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Multiple Time Series Perceptive Network for User Tag Suggestion in Online Innovation Community

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ABSTRACT User tag suggestion technique, aiming at learning users' preferences over knowledge products from their historical behaviors, plays an important role in generating personalized recommendation in online innovation community. However, most current user tagging solutions only utilize a single kind of behavior to predict a single tag for users, resulting in weak generalization of user profile. In this paper, we propose a multiple time series perceptive network (MTSPN) for user tagging tasks in online innovation community. In particular, MTSPN takes multiple kinds of user behaviors into consideration for collaborative perception purpose, in which multi-scale sequential features are extracted from different sequential behaviors, and a multi-label classification module is built-in the proposed MTSPN model to predict multiple tags for users. Our encouraging experimental results on a real-world dataset collected from "Thingiverse" community validate the superiority of the our MTSPN model over several existing user tagging methods.

INDEX TERMS User tag suggestion, multiple time series, perceptive network, online innovation community.

I. INTRODUCTION

With the rapid increase of knowledge products in the online innovation community, the need for personalized recommendation is occurring more and more frequently. User profile is a key technique to build a personalized recommender system. As a dominant technique to construct user profile, user tag suggestion (also called user tagging), aiming to perceive and describe users' preference based on their past interactions with products, has drawn substantial attention from both academia and industry.

Up to now, most of the existing user tag suggestion methods are designed for traditional recommendation scenarios, such as e-commerce, news and entertainment. Some earlier studies along this line are two-stage learning manner composed of feature engineering and classifier design [1]–[3], while others [15], [16] incorporate such two stages in end-to-end learning fashion.

Despite these success, conventional user tag suggestion solutions are limited by two shortcomings when deployed to the scenarios in online innovation community.

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1) Most existing methods focus on extracting or learning single feature from a specific kind of user behavior (e.g. purchased, collected or browsed) for tag prediction. However, there are many kinds of user behaviors in online innovation community, which jointly influence the users' preferences on knowledge products. Hence it is desirable to take multi-behavior into consideration to perceive users' preference collaboratively.

2) In the user tagging step, current methods are inclined to predict a single label for users according to the confidence of classifier. Such a manner is suboptimal, because a user is often interested in multiple categories of knowledge products in the online innovation community. In essence, the task of user tagging should be a multi-label prediction problem.

To address above problems, we propose a novel user tag suggestion scheme, termed multiple time series perceptive network (MTSPN), which predicts multi-tag for users by exploiting multiple kinds of user behaviors. First, we make statistics of different user behaviors according to the time granularity of day, month and year, and take multiple time series as the input of each branch of MTSPN. Second, we apply multiple Bi-LSTMs to learn multi-scale sequential features from multiple time series. Finally, we utilize a fully connected network to fuse such features, and feed them to a multi-label classifier to predict user tags, where the user tags are the categories of various knowledge products in the online innovation community.

We summarize the contributions of our work as follows:

1) Multi-behavior collaborative perception: MTSPN aims at learning multi-scale sequential features from multiple kinds of user behaviors, which can better perceive the diversity of users' information need;

2) Multi-label prediction for user tagging: MTSPN can predict multiple tags for users, which is beneficial to describe the users' multifaceted preference on knowledge products;

3) We construct a specialized dataset for the task of user tag suggestion in the scenario of online innovation community. Extensive empirical study on such a dataset shows encouraging results comparing to several existing user tagging methods.

The rest of this paper is organized as follows. Section II reviews the related works. In Section III, we describe our motivations and introduce our proposed MTSPN in detail. Experimental results and analyses are reported in Section IV. Finally, Section V summarizes our work.

II. RELATED WORK

Traditionally, for user tag suggestion task, the classic solution is to group users with similar features by using user attributes or user behaviors. Li *et al.* [4] proposed a purchase prediction method based on large-scale user behavior logs, which can predict users' "on-off line" purchase behavior in the future by using the integrated decision tree model. Zhong *et al.* [5] constructed a user tag library based on a large number of user attribute data, and used k-means algorithm to classify user groups. Chen *et al.* [6] and Liu *et al.* [7] proposed collaborative filtering recommendation algorithm based on user attribute clustering to predict user tags, respectively. Yao *et al.* [8] proposed a movie recommendation method based on user interest tags and browsing behaviors, which calculates the similarity between users and movies by using word2vec algorithm, and recommends the most similar movie to users. Subramaniyaswam and Logesh [9] proposed a recommendation algorithm based on adaptive KNN, which predicts user preferences by using user behavior and product attribute.

However, user grouping is not conducive to users' personalized recommendation. In addition, these classical methods ignore that the user behavior is a time series data, and the correlation between them is very important for perceiving user preferences. Therefore, these methods are not suitable for the user tag suggestion task in online innovation community.

In recent years, data processing methods based on machine learning have been applied in many fields and achieved many remarkable results [10]–[13]. Especially in deep learning, deep neural network [14] shows strong learning ability in time series feature representation, which gets to be the interest of both industry and academia. Gan and Xiao [15] proposed a model called recent recurrent neural network (R-RNN), which can adaptively predict user preferences according to users' historical click behavior. Beutel *et al.* [16] proposed a recommender system based on RNN, which uses latent cross technology to extract user context features, and integrates them into RNN model to improve the recommendation performance. Zhu *et al.* [17] proposed an improved long short term memory (LSTM) method to learn the correlation between users' adjacent behaviors, which can predict users' short-term and long-term interests. Chen *et al.* [18] proposed a transformer model based on attention mechanism to extract the features of user behavior sequence, which can be used to predict user preferences for the product. Zhong *et al.* [19] proposed multiple aspect attentive graph neural networks to extract user social network features, which can be used to generate user geographic information tag. Wang *et al.* [20] proposed a hybrid model based on deep belief network (DBN) and extreme learning machine (ELM) to analyze users' electricity consumption behavior.

However, the existing methods only use one kind of user behavior sequence data, and then predict a single label of the user according to the confidence of the classifier. In online innovation community, a single user behavior can not accurately represent user preferences, and a user is often interested in multiple categories of knowledge products.

In this paper, we propose MTSPN to perform user tag suggestion task in online innovation community. MTSPN can better perceive the diversity of users' information need, and can predict multiple user tags more accurately. Moreover, MTSPN is mainly focuses on modeling the interactions between users and product categories, rather than user-item interactions. Therefore, it can be easily extended for many online innovation communities, which has good generalization for user tag suggestion.

III. THE PROPOSED APPROACH

In this section, we first introduce the motivation of this work, followed by some necessary preliminaries, and then elaborate the details of the proposed MTSPN model.

A. MOTIVATION

In this paper, we mainly focus on the user tag suggestion task in online innovation community. To achieve this goal, we have analyzed the user behaviors of some existing online innovation communities, such as "Thingverse", "Github" and "ProductHunt". Although the user behavior designs of these community systems are different due to the different user groups and product categories, the means of their main user behaviors are similar. For example, "Like" in "Thingverse", "Star" in "Github" and "Upvote" in "ProductHunt" indicate that users are interested for a knowledge product. "Collect" in "Thingverse", "Fork" in "Github" and "Follow" in "Product Hunt" indicate that users may use and improve the knowledge products. "Design" in "Thingverse", "Create Project" in "Github" and "Submit" in "ProductHunt" refer to the knowledge products made by users. Therefore, there are necessary to

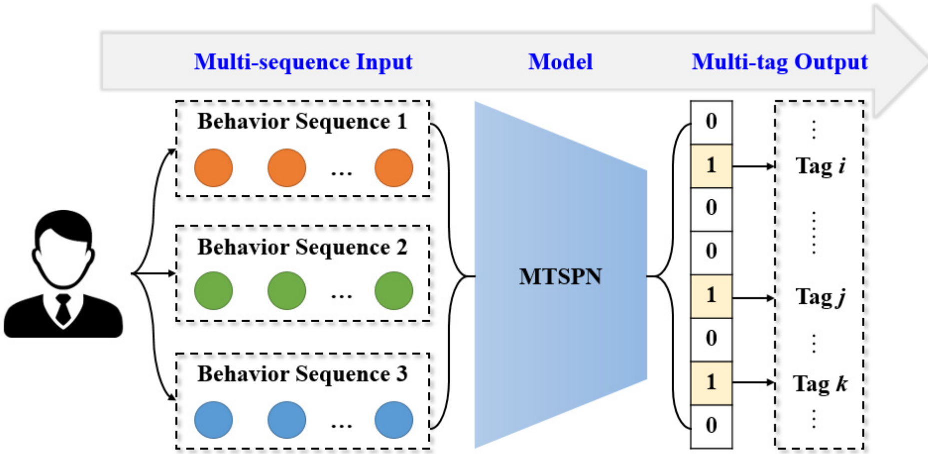

FIGURE 1. Overall framework of the proposed model for user tag suggestion in online innovation community.

use multiple user behaviors to perceive the changes of user preferences.

Significantly, the frequency of the above behaviors is very different. Specifically, in these online innovation communities, "Like, Star, Upvote" have a higher frequency, and users are likely to perform the above operations on many categories of knowledge products in one day. Subsequently, the frequency of "Collect, Fork, Follow" is relatively low, which are suitable for analysis by month. The frequency of "Design, Create Project, Submit" is the lowest, which need to be counted by year. Therefore, we need to use different time granularity to statistics these user behaviors, and extract multiple time series features by using time series data processing method.

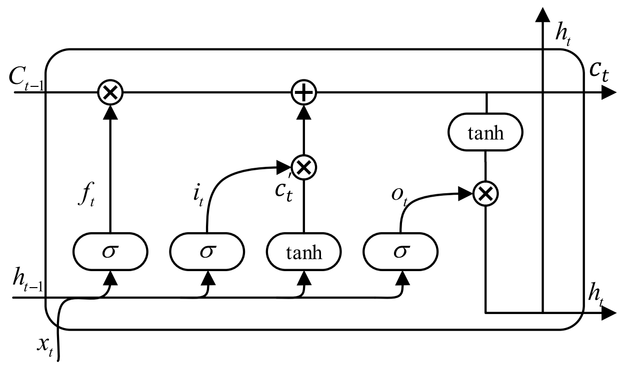

FIGURE 2. The hidden block calculation flow of LSTM.

B. PRELIMINARIES

Figure 1 illustrated the overall framework of MTSPN model that takes three kinds of user behaviors as inputs for learning multiple time series features, and outputs multiple tags for users in the form of multi-hot encoding.

Specifically, take "Thingverse" for example, $\mathrm{P}^u\mathrm{Q}^u$ and X^u are record the "Designs", "Collections", and "Likes" of u over a period of time. Each element in the collection is C dimensional vector, C represents the total number of knowledge product categories in the community. $\mathrm{P}^u = \left\{p_1^u, p_2^u, \ldots, p_Y^u\right\}$ indicates that the user u designs the number of products of each category in each year during the Y years; $\mathrm{Q}^u = \left\{q_1^u, q_2^u, \ldots, q_M^u\right\}$ indicates that the user u collects the number of products of each category in each month during the M months; $\mathrm{X}^u = \left\{x_1^u, x_2^u, \ldots, x_D^u\right\}$ indicates that the user u likes the number of products of each category in each day during the D days. L^u represents the output of the model, which is a C dimensional vector, and each element of L^u represents whether the user u prefers the knowledge products of the category in the future. The user tags can be obtained by mapping L^u to category names of knowledge products.

At present, how to use neural network technology to extract the features of time series information has become a recent trend in the community. Long short term memory (LSTM) [21] is an improved RNN model, which has strong learning ability in processing time series information. In order to learn the correlation between non-adjacent information, LSTM designs a unique block structure, which can make the network remember the output features of each block for a long time by inputting the output features of the previous block to the current block. The hidden block calculation flow of LSTM is shown in Figure 2.

C_{t-1} and h_{t-1} represent the output of memory unit and hidden block at previous time, respectively. x_t is input data at time t, $c_t^{'}$ represents the temporary memory unit, and its formula is as follows:

$$C_t' = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right), \tag{1}$$

where, b_c is the bias vector, W_c and U_c are the weight parameter matrix. f_t, i_t and o_t represent forgotten gate, input gate and output gate, respectively. Their calculation formulas are as follows:

$$\begin{aligned} f_t &= \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \\ i_t &= \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \\ o_t &= \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right), \end{aligned} \tag{2}$$

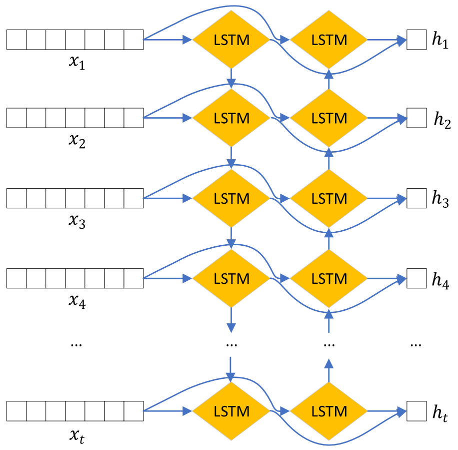

FIGURE 3. The calculation flow of Bi-LSTM.

where, W and U represent the weight parameter matrix of each control gate, respectively. b is the bias vector of each control gate.

C_t and h_t represent the output of the current memory unit and hidden block, which can be formalized as follows:

$$\begin{aligned} C_t &= i_t \otimes C_t' + f_t \otimes C_{t-1} \\ h_t &= o_t \otimes \tanh(C_t). \end{aligned} \tag{3}$$

where, $\otimes$ represents pointwise product. Both σ and tanh are activation functions, which can be calculated according to the following formulas:

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{4}$$

$$tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{5}$$

Although LSTM has made a lot of achievements in processing time series information, the output feature transfer of LSTM is unidirectional, which means that the output features of the current block is only related to that of the previous block, but not related to that of the next block. Obviously, LSTM is not suitable for the user tag suggestion task by processing user behavior information.

Bi-LSTM [22] adds the reverse feature transfer operation, and combines the results of two directions as the final output features, which can enable the network to learn the correlation between user behavior information at different times more fully, so as to improve the performance of user tag suggestion. Therefore, MTSPN selected Bi-LSTM to extract multi-time series features of user behavior. The calculation flow of Bi-LSTM is shown in Figure 3.

C. MTSPN

The network structure of MTSPN is shown in Figure 4, which is divided into four stages: multi-behavior collaborative perception, multi-scale sequential feature extraction, multiple time series feature fusion and user tag prediction.

In the stage of multi-behaviors collaborative perception, the three branches of MTSPN can accept three different types of user behavior information to construct the matrix

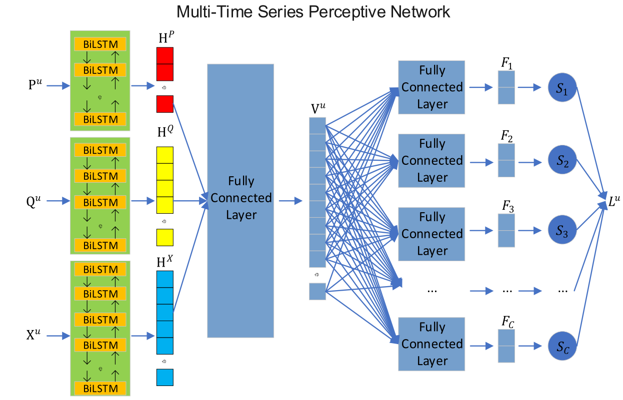

FIGURE 4. Network structure of MTSPN.

$P^u Q^u$ and X^u. Note that the time granularity of each matrix is different, but there are some correlations between them, which jointly influence the user personal preferences.

In the stage of multi-scale sequential feature extraction, three Bi-LSTM modules with different timestamps can extract the feature H^P, H^Q and H^X from the matrix P^u, Q^u and X^u, respectively. These different scale features represent the time series features of different behaviors of the same user.

In the stage of multiple time series feature fusion, a fully connected layer with 256 neurons is used to fuse three different scale feature vectors H^P, H^Q and H^X, and obtain 256-dimensional feature vector V^u. In addition, dropout strategy [23] is attached to the fully connected layer, which can randomly set the output of some neurons to 0 to prevent over fitting of the network model.

In order to realize the multiple user tags prediction, we use C fully connected layers with 2 neurons to transform V^u into $F^u = \{F_1, F_2, F_3, \ldots, F_C\}$. And then, F^u is input it to the multi-label classifiers $S = \{S_1, S_2, S_3, \ldots, S_C\}$, which can map F^u to the preference probability of user u for each category of knowledge products by using sigmoid function. Finally, the higher probability value of each classifier outputs is selected to form L^u as the final output.

For MTSPN training, the loss function is defined as follows:

$$\begin{aligned} Loss = &-\frac{1}{N}\sum_i^N \frac{1}{C}\sum_j^C \left(Y_j^{u_i} * log\left(\sigma\left(F_j^{u_i}\right)\right)\right) \\ &+ \left(\left(1 - Y_j^{u_i}\right) * log\left(1 - \sigma\left(F_j^{u_i}\right)\right)\right), \end{aligned} \tag{6}$$

where, N is the total number of training samples, C is the total number of knowledge product categories, $Y_j^{u_i}$ denotes whether the i-th user is interested in the j-th product category, and the value is 0 or 1. $\sigma(\cdot)$ is the sigmoid function, $\sigma\left(F_j^{u_i}\right)$ is the output of the classifier S_j, which represents the preference probability of the i-th user to the j-th product category.

IV. EXPERIMENTS

In this section, we carry out extensive experiments on a real-world dataset to verify the effectiveness of the proposed method comparing to several existing approaches.

A. DATASET

To our best knowledge, the publicly available datasets are not designed for the task of user tagging in the online innovation community. Therefore, we use web crawler to obtain a large number of real user behavior information data from Thingeverse community (www.thingiverse. com).

The dataset is established by recording the three most typical user behaviors, i.e., "Likes", "Collections" and "Designs". "Likes" include users appreciated material and products, which reflects the tendency of users to identify with the value of other people's products, and shows the positive emotions that the products bring to users. "Collections" include the products collected by users in their favorites, which tend to be instrumental. Such an attribute products indicate that users may review their contents repeatedly in the future, which is helpful for users to acquire knowledge. "Designs" include user design products, which is user's intuitive performance in expertise field. In Thingeverse, each product is assigned to a single specific category, which is also regarded as user tag.

The dataset contains 3 kinds of behaviors recording 80 categories of knowledge products sampled from 4000 users during the past 12 years, including 176458 like, 65078 collections and 22363 designs.

B. EXPERIMENTAL SETUP

For each user's historical behaviors, we select three behaviors before a specified time as the training input data according to timestamps, and use the knowledge product category corresponding to the behaviors after that time as the user tags. For example, the network model of timestamps $T = (7, 3, 2)$ means using a user 7-day "Likes", 3-month "Collections" and 2-year "Designs" before a specified day as training input data, and using the knowledge product categories corresponding to 7-time "Likes", 3-time "Collections" and 2-time "Designs" behaviors after that time are used as the user tags. For all data, we use the first 80% data to train the model, 10% data is used to as the valid set, and the last 10% data is used to evaluate the model performance.

We select several existing methods as the baseline, which are popular in user tag suggestion and recommender system.

- XGboost [3]: This method constructs decision tree by user behavior sequence, and boost multiple decision trees for feature selection. Finally, the user tag is predicted by logistic regression.
- DBN [20]: This method takes one kind of user behavior as the input sequence, and uses multiple hidden layers to extract features, so as to realize the correlation learning of adjacent behaviors. The user tag is predicted by Softmax.
- RNN [15] and LSTM [17]: RNN is an effective time series data processing method, which can extract time series features by connecting multiple hidden units in sequence. In RNN, each hidden unit simultaneously receives the input data of the current time and the output data of the previous hidden unit. LSTM is an upgraded version of RNN, which solves the vanishing gradient problem of RNN in back propagation by adding several control gates.

In the training of XGboost and DBN, we train three models for three kinds of user behaviors respectively, and use the voting method to count the prediction results of the three models to get the final user tags. The general hyper parameters of training are followed the settings reported in their papers, and we only modify some specific settings to adapt to our data, such as the number of input leaf nodes or neurons.

In the training of RNN, LSTM and MTSPN, we use the same end-to-end framework to predict user tags. The stochastic gradient descent (SGD) algorithm is used to iteratively optimize the weight parameters of each layer of the model. The momentum is set to 0.9, and the weight attenuation factor is set to 0.0005. The weight parameters of each layer are initialized by Kaiming regularization [24]. The activation function of the fully connected layers is selected as PRelu [24], and the dropout ratio is set to 0.3. We set the initial learning rate as 0.01. When training to the 20th, 40th, 60th and 90th epochs, we reduce the learning rate by 10 times, and the total training epochs is 100.

In this experiment, we used recall rate, F1 score and mean average precision (MAP) as evaluation indicators.

C. RESULT ANALYSIS

In order to prevent experimental errors, we repeat the experiment 10 times, and the timestamps are set to $T = (12, 5, 3)$. Table 1 illustrates the quantitative results in terms of MAP, Recall, F1-Score performed by different methods on test set, where the best performance is boldfaced. AVG and SD represent the average value and standard deviation, respectively. Several observations can be drawn from the experimental results.

- By examining the results of all methods, we find that all end-to-end feature learning solutions (RNN, LSTM and MTSPN) outperform the two-stage solution XGboost and DBN. This observation demonstrates that end-to-end learning style is beneficial to the user tag suggestion task.
- By comparing DBN with RNN, LSTM and MTSPN, we observe that three sequential models (RNN, LSTM and MTSPN) achieve better performance than DBN, which verifies the effectiveness of sequential features.
- Comparing RNN with LSTM, we find that each performance index of LSTM is improved by nearly 20%, which shows that LSTM can better learn the correlation between different time series features, and the extracted multi-scale sequential features are more conducive to predict user tags.
- Among three sequential models (RNN, LSTM and MTSPN), it is impressive that MTSPN consistently outperforms others. Compared with RNN, MTSPN's MAP @ 5, @ 10, recall @ 5, @ 10 and f1-score @ 5, @ 10 increased by 58.4%, 52.7%, 51.2%, 50.7%, 54.9% and 51.7%. Compared with LSTM, the growth rates of

TABLE 1. Performance comparison of MTSPN and other compared methods with timestamps t = (12, 5, 3), evaluated by recall, F1-score and map.

Method	MAP@5/%		Recall@5/%		F1-Score@5		MAP@10/%		Recall@10/%		F1-Score@10	
	AVG	SD	AVG	SD	AVG	SD	AVG	SD	AVG	SD	AVG	SD
XGboost[3]	0.3241	0.1383	0.3756	0.2056	0.3481	0.0017	0.3132	0.2124	0.3755	0.2312	0.3416	0.0017
DBN[20]	0.4350	0.2022	0.4953	0.1698	0.4632	0.0016	0.5352	0.2239	0.5787	0.1271	0.5561	0.0014
RNN[15]	0.4819	0.1399	0.5433	0.1530	0.5107	**0.0008**	0.5819	0.1423	0.6124	0.1250	0.5967	0.0013
LSTM[17]	0.6922	0.1625	0.7787	0.1671	0.7329	0.0013	0.8338	0.2275	0.8848	0.1727	0.8585	0.0019
MTSPN	**0.7631**	**0.1019**	**0.8216**	**0.1081**	**0.7913**	**0.0008**	**0.8883**	**0.1343**	**0.9231**	**0.1173**	**0.9053**	**0.0012**

In Table 1, @ K represents the threshold value of correct prediction, that is, the error term < = k between the predicted tags of 80 categories by the model and the real tags of each user.

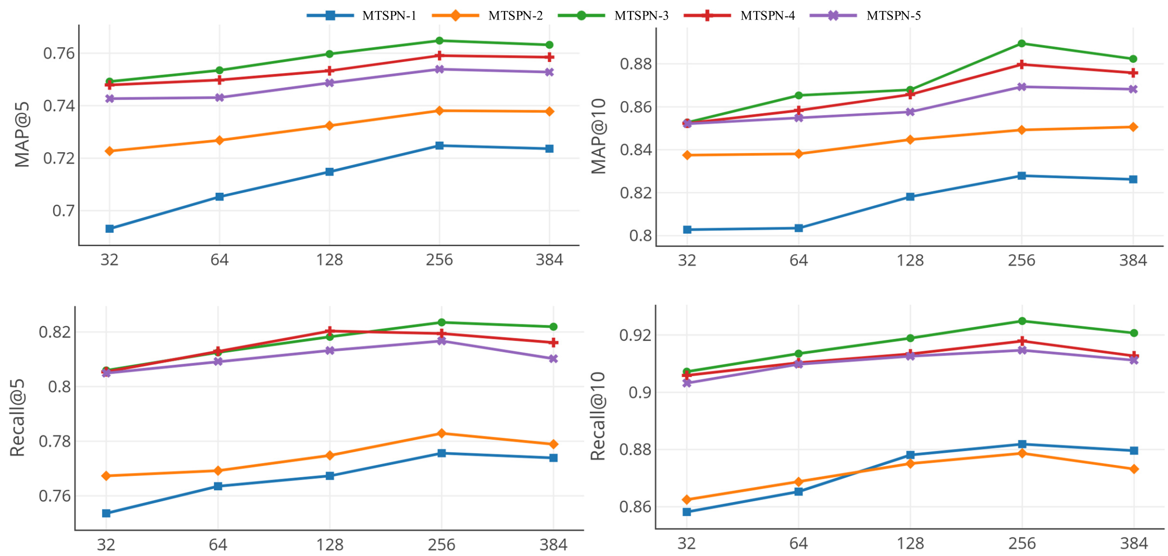

FIGURE 5. Experimental results of MTSPN performance comparison under different hyper parameter settings.

the above indicators were 10.3%, 6.5%, 5.5%, 4.3%, 8.0% and 5.5%. This observation shows that the proposed method can better learn the correlations between multi-scale sequential features through Bi-LSTM.

D. HYPER PARAMETERS DISCUSSION

In order to study the influence of the hyper parameters timestamps T and the neurons number d of the fully connected layer on the model results, we use different values of T and d for comparative experiments. To be specific, we set up five kinds of selection schemes of timestamps, MTSPN-1: $T = (7, 3, 2)$; MTSPN-2: $T = (7, 4, 2)$; MTSPN-3: $T = (12, 5, 3)$; MTSPN-4: $T = (15, 5, 3)$; and MTSPN-5: $T = (20, 6, 4)$. The number of neurons d in the fully connected layer is set as 32, 64, 128, 256 and 384, respectively. The comparative experimental results are shown in Figure 5.

According to the experimental results, MTSPN-2 only uses more "Collections" behavior for one month than MTSPN-1, but it significantly improved the MAP and recall, which indicates that "Collections" behavior has a greater impact on user preferences. Compared with the first two schemes, the latter three schemes greatly improved the overall performance of MTSPN due to the use of user behaviors for a longer time, and the performance is the best in the third scheme. In addition, although the fourth and fifth schemes use more user behaviors, the prediction performance of the model has not significantly improved, which indicates that the user behavior has a timeliness, and the user behavior with longer interval has less impact on the current user preferences.

Different neurons number d of the fully connected layer can generate the feature vectors with different dimensions for user behavior, which represents the fusion degree of MTSPN to multi-time series features. The experimental results show that the performance of MTSPN is positively correlated with d, and it reaches the optimal when $d = 256$. The fusion degree of multi-time series feature influences the prediction results of MTSPN, and the appropriate fusion degree can significantly improve the model performance, nevertheless, a higher dimensional feature may cause the model to overfit, resulting in performance degradation. Therefore, in practical applications, the neurons number in the fully connected layer should be selected flexibly according to the complexity of user behaviors.

V. CONCLUSION

In this paper, we proposed a novel method for user tagging in online innovation community, called multiple time series perceptive network (MTSPN), which predicts user tags in an end-to-end learning fashion. Specifically, MTSPN makes full use of the users' multiple behaviors for collaborative perception, and considers the correlation between different times and different types of behaviors to extract the multi-scale sequential features. Extensive experiments demonstrated that the proposed method achieves considerable performance over several existing user tag suggestion approaches. Our future work will analyze the model interpretability by introducing attention mechanism.

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